

CROSS-CLASS CORRELATION AND ASSET ALLOCATION:

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This paper was originally presented to the RICS “Cutting Edge” Research Conference, held in Cambridge, UK, September 1999. This current version benefits from comments made at the conference and by numerous colleagues. Please contact the authors prior to any quotation lest there be a later version available. Current revision 7 November 2000.

Abstract

Practical applications of portfolio optimisation tend to proceed on a “top down” basis where funds are allocated first at asset class level (between, say, bonds, cash, equities and real estate) and then, progressively, at sub-class level (within property to sectors, office, retail, industrial for example). While there are organisational benefits from such an approach, it can potentially lead to sub-optimal allocations when compared to a “global” or “side-by-side” optimisation. This will occur where there are correlations between sub-classes across the asset divide that are masked in aggregation – between, for instance, City offices and the performance of financial services stocks. This paper explores such sub-class linkages using UK monthly stock and property data. Exploratory analysis using clustering procedures and factor analysis suggests that property performance and equity performance are distinctive: there is little persuasive evidence of contemporaneous or lagged sub-class linkages. Formal tests of the equivalence of optimised portfolios using top-down and global approaches failed to demonstrate significant differences, whether or not allocations were constrained. While the results may be a function of measurement of market returns, it is those returns that are used to assess fund performance. Accordingly, the treatment of real estate as a distinct asset class with diversification potential seems justified.

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KEYWORDS: portfolio allocation, asset classes, top down strategies, optimisation.

1. Introduction

The principle underlying mixed asset portfolio optimisation is that combinations of assets with less than perfect positive covariance produce portfolio variances that are less than those suggested by the individual asset variances. This risk diversification effect results from the differential impact of performance drivers across the assets or from differences in the timing of those impacts. Theoretically, in determining optimum allocations, all individual investment assets should be considered simultaneously. However, this ideal is rarely met in practice, not least due to the absence of individual level real estate data. Typically, investors (particularly institutional investors) will use formal allocation models to allocate at asset class level (that is, between equities, bonds, real estate and other classes of assets) and then appoint specialist managers whose task is to optimise the asset class portfolio. Such an organisational approach has been described as a “top down” allocation strategy. Real estate research has largely followed this structure, studies either being concerned with the “correct” allocations to property within the mixed asset portfolio or with the optimal diversification strategy within real estate considered in isolation.

The portfolios that result from a top down allocation strategy might be sub-optimal. This would be the case where strong positive correlations between individual assets or sub-sectors *across* the asset class divide are ignored. Cross-asset class relationships would result from common performance drivers. For example, consumer spending should drive the profits of retailers and be reflected in the share returns of retail firms. A share of those profits are captured by landlords and this should be reflected in the property market performance of shops. Similarly, City of London office market performance might be expected to exhibit correlation with financial service firm share performance (and, indeed, be more closely correlated to overall equity market performance) and there might be links between manufacturing industry and industrial real estate. These relationships might well be masked when the asset class data is aggregated. Asset class “fund” managers might thus allocate capital to such assets, myopic to the actions of other fund managers. As a result, the degree of risk diversification may be reduced. An alternative view might be that the institutional structure of the property market and the specific characteristics of real estate as an investment asset will mean that there is a distinct “property factor” which will dominate any cross asset class relationships.

This paper seeks to investigate this issue. Using monthly data for sub-sectors of the commercial real estate market and the equity market in the UK, we seek to determine if there are, indeed, cross-asset correlations that might lead to sub-optimal allocations using a top-down approach. We then examine whether or not portfolios determined by a two-stage optimisation process are inferior to those derived from a single stage “side by side” approach. The analysis presented here has similarities with the country versus industry structure research undertaken in international stock markets (see, for example, Drummen and Zimmerman, 1992) and market segmentation studies such as that by Cuthbertson *et al.* (1999).

The next section details the data employed in the study and the transformation procedures employed to identify true property market performance. Section three examines the relationships that exist between asset classes and between sub-sectors within and across asset classes. The fourth section presents portfolio results from constrained and unconstrained optimisations using top-down and side-by-side approaches. Finally, conclusions are drawn and further research routes identified.

2. Data Utilised

To obtain as large and frequent a time series as possible, real estate data was drawn from the Investment Property Databank (IPD) monthly index. Index values for the period December 1986 to December 1998 were obtained. The broad three sector/region classification employed by IPD was utilised. However, for London offices a finer geographical split was used, separately analysing City, West End and Outer London offices. The sub-division reflected both the importance of central London offices in institutional portfolios and possible *a priori* linkages between City of London offices and the financial sectors in the stock market. This resulted in eleven property sectors for analysis. These are listed in Figure 1.

Figure 1: Property Sectors Analysed

Offices: City of London
Offices: West End
Offices: Outer London
Offices: South East
Offices: Rest of UK
Retail: London
Retail: South East
Retail: Rest of UK
Industrial: London
Industrial: South East
Industrial: Rest of UK

For equity data, sectoral return indices based on the FTSE Actuaries Industry Classification system were extracted at two digit level from Datastream. Fifteen sectors were chosen for analysis (to provide a similar number of sectors as for property, to avoid variable bias in subsequent analysis), the choice based on market capitalisation. The small Real Estate sector (property companies and agents) and Construction and Building were included since, *a priori*, these might be expected to have linkages to the direct real estate market and Food and Drug Retailing was included for its potential links with retail property. Utilities were combined together into a single category. The sectors selected had a combined market capitalisation of £1,134billion at end 1998, representing 80% of the capitalisation of the All Share Index. Figure 2 lists the selected sectors with their market capitalisation.

The property and equity series were converted to logged differences and deflated, using the Retail Price Index, to approximate a real returns series for each sector. As expected, the IPD monthly series exhibits strong serial correlation (this is generally attributed to appraisal smoothing). First order serial correlation coefficients ranged between 0.56 and 0.76. Accordingly, the series was desmoothed. The approach adopted here was that of Geltner (1993) as it makes no assumptions about the efficiency of the real estate market. Similar problems were not encountered with the stock series.

Figure 2: Stock Sectors and Market Capitalisations

Sector	Capitalisation (£bn., Dec 1998)
07 Oil and Gas	128.8
13 Construction & Building Materials	28.8
26 Engineering & Machinery	46.0
43 Food Producers & Processors	47.2
48 Pharmaceuticals	150.7
52 General Retailers	52.0
54 Media & Photography	59.3
58 Support Services	49.2
63 Food & Drug Retailers	34.4
67 Telecommunication Services	137.3
70 Utilities	87.0
81 Banks	204.2
83 Insurance	42.1
84 Life Assurance	46.3
86 Real Estate	21.1
TOTAL	1134.4

It is possible to identify hypothetical prior expectations of relationships between sub-classes across the asset divide. *A priori*, one might expect a relationship between retail property performance and the performance of general and food retailers. Higher consumer expenditure should both boost the profitability of the firms and feed into higher rental income (even in the absence of turnover rents). Expectations of future growth should lead to expectations of dividend and rental growth boosting share prices and, through lower initial yields, provide capital growth. The linkage should be strongest in the larger south east market. One might expect a relationship between City of London offices and financial services share performance, particularly in non-retail areas. The linking mechanism might be through strong financial market performance leading to employment growth, the greater demand for space leading to rental increases. Other possible linkages might be between industrial property and engineering and manufacturing firms or between telecommunications and south east office and industrial property. While such relationships are plausible, the approach adopted here is exploratory, allowing any linkages to emerge from the empirical analysis.

Caveats are necessary concerning the real estate data. First, it is appraisal based. As noted above, the data has been desmoothed in an attempt to remove induced serial correlation. Nonetheless, the residual signal may imperfectly represent “true” property market performance. This has led some authors to reject the use of appraisal data. We note, however, that the performance of institutional investors is judged on such data. Relative fund performance, benchmarking, portfolio strategy, property unit trust unit price, bonus calculation are all based on appraisals and are assessed on an annual or more frequent basis in the absence of extensive transaction evidence. It may be misleading, therefore, to base investment decisions only on public market data when the target asset class is private. Second, the IPD monthly index is dominated by property unit trusts. The relatively small size of such trusts means that there exist entry barriers in certain markets: notably for prime City of London and West End offices and for shopping centres. This may, therefore, mask some cross-asset sub-class relationships. Unfortunately, no alternative data source exists.

3. Asset Class and Sub-Class Behaviour

Correlation Structures

As a first step, the contemporaneous correlation matrix¹ was examined to see if there exist contemporaneous linkages between sector returns across the asset class divide. Within asset class, significant positive correlations exist. For the real estate sub-sectors, all correlations were significant at the 0.01 level, averaging 0.45. Consistent with our knowledge of stock market performance, equity market sub-sector returns exhibit still stronger internal correlations, averaging 0.62. Across asset classes, the vast majority of correlations are statistically indistinguishable from zero. The only correlations significantly different from zero at the 0.01 level are those between City of London Offices and Property Companies (0.22), Construction (0.22) and between Outer London offices and Telecommunications (0.23). A handful of others are significant at the 0.05 level, but no obvious patterns are discernible.

Cluster Procedures

The correlation results clearly suggest that property and equity market sub-class returns have strong common elements and weak cross-class linkages. The results of cluster analytic tests confirm this assumption. To avoid biases resulting from choice of technique or distance metric, a variety of techniques (using both agglomerative and group allocation models) were tested and gave consistent results. Here, the results of a hierarchical, agglomeration using Ward's linkage procedure and the K-means approach are reported.

For the hierarchical procedure, the within-groups sum of squares criteria points to two distinct groups – split exactly along asset class lines with all property sub-sectors in one group, all stocks in the other. The real estate sub-sectors join together early in the fusion process, with successive property sub-sectors merging into a single group. The last to merge are the West End and City of London office markets. This may indicate that the performance of the central London office market is, to some extent, distinct from other segments of the market. Within the stock market sectors, a “financials” cluster emerges as does a general retail and consumer services grouping and an “industrial” grouping. Curiously, property companies and oil & gas cluster together (albeit at a late stage in the fusion process). This result is persistent.

Figure 3: Hierarchical Clustering: Six Group Solution

Cluster One (11):	All Real Estate Sub-Sectors
Cluster Two (2):	Oil & Gas; Property Companies
Cluster Three (3):	Construction; Engineering; Media & Printing
Cluster Four (6):	General Retailing; Food & Drug Retailing; Food Processing; Support Services; Telecommunications; Utilities
Cluster Five (1):	Pharmaceuticals
Cluster Six (3):	Banks; Insurance; Life Assurance

Using the K-Means procedure with six groups produces near identical results. Once again, all real estate sub-classes are together in one group, Pharmaceuticals is in a single member group and Oil &

¹ Available from the authors.

Gas and Property Companies group together as do Construction; Engineering; Media & Printing. However, General and Food and Drug Retailing form a distinct cluster with the remaining consumer and financial sectors combining together.

Property and Equity Dimensions

In an attempt to identify common patterns of variation in the data, the returns were analysed using factor analytic procedures. The results reported here result from a principal components analysis of the asset sub-sectors, followed by an orthogonal (varimax) rotation of a set of retained factors intended to maximise factor loadings on individual sectors and hence aid interpretation. Initially, all factors with eigen values equal to or greater than one were retained (three factors in total, explaining 65% of the variance in the data). A second analysis, based on the scree test, retained the first six factors (explaining 75% of total variance).

The factor loadings for the rotated three factor solution are showed in Figure 4, below. The first two components clearly identify variation relating to the two asset classes. The first is a Stock Market factor, with all equity sub-classes having loadings in excess of 0.6. The second component is equally clearly a property factor, with only City Offices failing to load strongly (City Offices has the highest loading on the Stock Factor of all the property sub-sectors). The third factor has no obvious interpretation. The factor analysis literature suggests that the final retained component acts as a “clean up” factor for the remaining variance, so this may not be surprising.

However, the rotated solution with six retained components² provide some more clarity and match the findings of the cluster analysis. Component three has higher loadings in Telecommunications and Utilities stocks; City and West End offices load highly onto the fourth component and the industrial property sectors of the South East and Rest of UK have higher loadings on component five. The sixth again cleans up the remaining variation. Even here, the lower components split into property and equity factors. It should be noted that the proportion of variation explained by the lower order components is very low – component three and four each explain 4% of variance, component five just 3%. The first two components explain 61% of variance, providing strong evidence of a (contemporaneous) asset class effect. Factor scores from the first two variables were retained for further analysis.

² A Factor Loading table is available on request from the authors.

Figure 4, Factor Loadings, 3 Retained Factors, Varimax Rotation

Sector:	Component One	Component Two	Component Three
City Offices	.188	.540	-.311
W End Offices	-.032	.618	-.234
O London Offices	-.059	.619	.287
SE Offices	-.006	.771	-.085
Rest UK Offices	.000	.819	-.027
London Retail	-.067	.757	-.021
SE Retail	.075	.794	.108
Rest UK Retail	.032	.873	.170
London Industrial	.062	.599	.037
SE Industrial	.098	.720	-.036
Rest UK Industrial	-.077	.848	.109
Oil + Gas	.766	-.052	-.009
Construction	.871	.017	-.219
Engineering	.867	.024	-.248
Food Process	.870	.046	.057
Pharmaceuticals	.661	-.017	.271
General Retailing	.832	-.041	.174
Media + Print	.911	.025	-.127
Support Services	.886	.093	-.051
Food + Drug Retail	.648	.050	.356
Telecommunications	.682	.126	.456
Utilities	.639	.076	.545
Banks	.833	.042	.189
Insurance	.846	.080	.099
Life Insurance	.793	-.003	.197
Property Companies	.831	.073	-.125

Evidence of Cross Asset Class Linkages

The first two components identified using factor analysis can be used as composite measures of “property” and “equity” performance. While it might be possible to use conventional market indices (e.g. the IPD monthly index and the FTA All Share Index), there are advantages in using the factor scores. First, the components have been orthogonalised, eliminating any possible (albeit small) multi-collinearity. Second, stock performance on the FTA may be influenced by the substantial property holdings of listed firms (an issue identified in Lizieri & Satchell, 1997). The individual sub-sector returns were then regressed on the two component factor scores in a zero constant model:

$$S_{jt} = \beta_j F_{st} + \gamma_j F_{pt} + v_{jt}$$

Where S_{jt} is the return for sub-sector j at time t , F_{st} is the factor score for the stock component at time t and F_{pt} is the factor score at time t for the property component. We interpret the residual v_{jt} as representing the return variation for the sub-sector additional to that induced by the two market factors. If there are common return patterns between sub-sectors across the asset class divide, then removal of the “property” and “stock” factors may allow them to be isolated and identified.

Figure 5, Coefficients from Two Factor Regression

Sector:	Adjusted R ² *	Stock Factor Coeff. (t-statistic)	Property Factor Coeff. (t-statistic)	D-W statistic
City Offices	.24	.007 (2.71) @@@	.017 (6.26)	2.28
W End Offices	.13	-.003 (-0.89)	.013 (4.51)	2.50
O London Offices	.51	.001 (0.92)	.018 (12.14)	2.49
SE Offices	.50	.001 (0.28)	.024 (12.14)	2.73
Rest UK Offices	.56	.000 (0.20)	.025 (13.42)	2.57
London Retail	.65	-.000 (-0.36)	.020 (16.21)	2.42
SE Retail	.53	.002 (1.16)	.018 (12.79)	2.75
Rest UK Retail	.70	.001 (0.55)	.022 (18.29)	2.21
London Industrial	.16	.002 (0.79)	.011 (5.30)	2.53
SE Industrial	.22	.002 (0.91)	.014 (6.37)	2.43
Rest UK Industrial	.73	-.002 (-1.53)	.029 (19.63)	1.91
Oil + Gas	.56	.045 (13.48)	-.005 (-1.40)	2.18
Construction	.81	.065 (24.65)	.002 (0.82)	2.01
Engineering	.81	.062 (24.65)	.002 (0.69)	1.97
Food Process	.74	.043 (19.90)	.004 (1.66) @	1.84
Pharmaceuticals	.35	.041 (8.84)	-.003 (-0.78)	1.82
General Retailing	.65	.045 (16.35)	-.000 (-0.15)	2.27
Media + Print	.84	.062 (27.87)	-.000 (-0.22)	1.79
Support Services	.77	.052 (22.02)	.002 (1.19)	2.07
Food + Drug Retail	.36	.033 (9.90)	.003 (0.68)	1.95
Telecommunications	.37	.037 (9.15)	.008 (1.89) @	1.74
Utilities	.29	.033 (7.71)	.004 (0.88)	2.15
Banks	.61	.006 (14.99)	.001 (0.27)	1.80
Insurance	.69	.058 (17.73)	.006 (1.78) @	1.76
Life Insurance	.54	.048 (13.11)	-.001 (-0.37)	1.75
Property Companies	.67	.055 (17.37)	-.000 (-0.12)	1.91

Notes: * with zero constant, measures the proportion of the variability in the dependent variable about the origin explained by regression;

@ cross-class correlation significant to the 0.10 level;

@@@ cross-class correlation significant to the 0.01 level.

The coefficients from the series of regressions are shown above, along with the adjusted R-squared and Durbin-Watson statistics. The results once again confirm the dominance of asset class factors. Of the property sub-sectors, only City offices has a statistically significant beta for the stock component (in an equation with a low R² value). Three equity market sectors have weakly significant (at the 10% level) gamma coefficients for the property component: food production, telecommunications and insurance. Sectors that might have been expected to show property linkages - construction, general retailing, property companies, for example – have gamma coefficients indistinguishable from zero.

Next, the residuals from the regressions, as proxies for sub-sector factors, were analysed. First, the correlation matrix was examined. As might be expected, correlation coefficients are generally low. Around 25% of correlations are significant at the 0.05 level – however, it should be noted that, given the number of observations, the threshold value is only 0.165. About 17% are significant at the 0.01 level but only six coefficients exceed 0.4 and none exceed 0.5. Thus the two market factors have captured most of the variation. Examining correlations for pairs of assets across the asset class divide, only eight are significant at the 0.01 level. No obvious groupings emerge although Telecom and Utilities have the highest correlation (0.493) and all the financial sectors have significant positive correlations.

The results of hierarchical clustering analysis on the residual returns confirm the pattern of the correlations. No clear breaks emerge. As clusters form, all property sectors except the West End and City office markets (which form a distinct cluster) and Outer London offices fuse, there is a financials sector (banks, insurance, life assurance), a group of “consumer” stocks (general and food retailing, telecommunications, utilities and pharmaceuticals) with other sub-classes remaining distinct until late in the fusion process or join into small groups with no obvious interpretation. Grouping using the K-means procedure fails to add clarity. There is one large group, including all the property sectors and a number of equity sectors; a financials group; telecommunications and utilities; general and food retailing³; oil & gas and property companies once again cluster; finally, pharmaceuticals is a stand-alone category. Principal components analyses of the residuals fail to generate easily interpretable results although there is weak evidence for a financial factor and a telecommunications-utility factor. No factors with high loadings on both property and stock sub-sectors emerge.

4. Lagged Effects and Granger Causality

It is possible that the failure to identify common patterns of performance across the asset class divide results not from absence of common drivers but from lags in the transmission mechanism. As a preliminary test, the relationship between the property and the stock factors were examined with different lag structures (recall that the factors result from an orthogonal rotation so that the contemporaneous correlation should be zero). Regression models were run with the general form:

$$\begin{aligned} F_{st} &= f[F_{pt}, F_{pt-1}, F_{pt-2}, \dots, F_{pt-m}] \quad \text{and} \\ F_{pt} &= f[F_{st}, F_{st-1}, F_{st-2}, \dots, F_{st-m}] \end{aligned}$$

The results provided no great evidence of a lagged effect. There was a weak positive correlation between the property factor and the stock factor lagged three months, (significantly different from zero at the 0.06 level) but no other effects were discernible. The property factor did not affect the stock factor. The lagged price discovery effect observed by Barkham and Geltner (1995) or the Granger causality results found by Lizieri and Satchell (1997) were not observed in this analysis⁴. Use of the sum beta, as suggested by Dimson (Dimson, 1979; Dimson & Marsh, 1983) to see if there are accumulative lagged effects did not alter this conclusion. Examining autocorrelations, the stock factor provided evidence of mean reversion, with a significant negative coefficient at lag 2 (Box-Ljung significant at the .03 level) with a further, weaker, negative coefficient at lag 3. The main feature of the property factor autocorrelations was a strong positive coefficient at lag 12 (Box-Ljung significant at 0.001 and beyond). Presumably this is some form of appraisal effect.

A series of pairwise Granger causality tests were run in order to investigate any leading and lagging relationships. First, the stock and property factors were tested against the residual sub-sector series from the other asset class. Next the sub-sector returns were examined and, finally, tests were run on the residual sub-sector series. To avoid data mining, the lag length was fixed at twelve (consistent with

³ The Stock Exchange’s distinction between cyclical and non-cyclical industries does not seem to be mirrored in performance.

⁴ In contrast, the FT All Share index appears to Granger-cause the IPD monthly index in smoothed and unsmoothed forms: $F = 2.592$ ($p=0.005$) and $F = 2.478$ ($p=0.007$) respectively.

the Barkham and Geltner (1995) price discovery result and sufficiently long to remove autocorrelation effects). Tests were only run on pairs of variables where there was a prior expectation of a possible cross-asset relationship.

As Panel 1 of Figure 6 shows, the stock factor Granger causes four of the eleven residual property sub-sectors: City Offices, South East Offices, London Industrial and London Retail. Of these, three are readily explicable: City of London and South East office demand is driven in large measure by financial and business services, while the performance of the stock market influences consumer spending in the London region. Lagged adjustment between the demand signal and rents and values creates the lead-lag relationship. It is, however, harder to explain why London industrials (and not other regional industrials) have an effect. Examining other lags suggests that the result is unstable and may simply be an artefact of outlying values. The lead that peripheral UK offices exhibit over the stock factor is, similarly hard to rationalise.

Panel 2 of Figure 6 reveals that five stocks appear to lead the property factor: Property Companies, General Retailing, Food Retailing, Utilities and Pharmaceuticals. The property company result is consistent with prior studies of price discovery between public and private markets. The remaining stocks are all in activities that lead to demand for space (shopping space, R+D and industrial space) or are associated with increased industrial activity. It is not clear, however, why these, and not other, residual stock returns generated significant results. The property factor did not Granger cause any of the residual stock series.

Figure 6: Granger Causality Tests: Stock and Property Factors

<i>Panel 1: Stock Market Factor compared to Residual Property Sub-Sectors</i>		
Significant results:		
Stock Factor Granger Causes:	City Offices	F = 2.001 (p = 0.031)
	South East Offices	F = 1.963 (p = 0.035)
	London Industrial	F = 3.271 (p = 0.001)
	London Retail	F = 2.119 (p = 0.021)
Rest of UK offices Granger Causes:	Stock Factor	F = 1.944 (p = 0.037)
<i>Panel 2: Property Market Factor compared to Residual Stock Sectors</i>		
Property Factor is Granger caused by:	Property Companies	F = 1.849 (p = 0.049)
	General Retailing	F = 1.891 (p = 0.043)
	Food Retailing	F = 2.042 (p = 0.027)
	Utilities	F = 2.185 (p = 0.017)
	Pharmaceuticals	F = 2.380 (p = 0.009)

For the paired sub-sector causality tests, it was hypothesised that there could be Granger causality (independent of overall stock and real estate effects) between:

- City of London offices and financial stocks (the City is strongly functionally specialised in international financial services);

- London and south eastern retail property and financial stocks (it is argued that financial service performance fuels consumer expenditure in the capital);
- West End offices and media stocks (a key employment sector in that part of London);
- Retail real estate and retail stocks (consumer expenditure fuels retail profitability and determines ability to pay rent);
- South east office & industrial property and telecomms, support services, utilities & pharmaceutical stocks (key employment sectors in the outer metropolitan area);
- Rest of UK industrial and engineering stocks (more traditional manufacturing activity is generally peripheral in location);

Examining the relevant pairs of variables using the residuals from the factor regressions, little evidence of Granger causality was found. City offices were not Granger caused by any of the financial stocks. South east and London retail are not Granger caused by financial stocks (insurance stocks weakly Granger cause London retail [$F = 1.71$, $p = 0.074$] but the relationship is unstable and may simply reflect common outliers). General retail stocks Granger cause retail property in the Rest of the UK ($F = 2.87$, $p = 0.002$) but not in London and the south east. Media stocks weakly Granger cause West End offices ($F = 1.74$, $p = 0.076$). Utilities shares Granger cause south east industrial property ($F = 1.85$, $p = 0.05$) as do pharmaceutical stocks albeit weakly; however, there is a weak Granger causality *from* south east offices *to* telecomms and utilities shares (both significant at around the 10% level). This might result from the lagged demand for office infrastructure and services, with pre-letting of space common in boom periods in the south east of the UK. Similarly, Rest of UK industrial property weakly Granger causes utility stocks.

While these results are plausible, they are not strong. All other selected pairs revealed no Granger causality. Of twenty seven tests performed, in just eight cases was Granger causality found at the 10% level or below. Indeed, with only two tests proving significant at the 0.05 level, the results could be attributed to random sampling effects. Thus, it would seem that, even at sub-class level, real estate and equities are quite distinct as *investment* assets. This is not to deny that there may be common return drivers. However, lagging effects and institutional factors such as lease contracts mean that the return performance is distinctive. We reiterate that, while there may be doubts about the validity of the appraisals that form the basis of the real estate returns, it is the appraisal-based data that is used in performance measurement and benchmarking and, hence, is a key measure in asset allocation.

5. Mixed-Asset Allocation

The results in the previous section suggest that the major asset classes, Equities and Real Estate, react independently of each other in terms of their risk return performance. This implies that each asset class can be treated as an investment fund in its own right. This suggests a two-stage investment selection process. That is monies are first allocated between the main asset classes Equities, Bonds and Real Estate and then the investment within each asset class is undertaken.

Intra-fund allocations following a similar approach. For example in the real estate portfolio this would entail the allocation of funds across the three property sectors (Offices, Shops and Industrials) followed by a region allocation and finally the purchase of individual properties. In other words the investment decision process becomes one of investment in m mutually exclusive funds as represented

by the major asset classes with the management of each ‘fund’ allocated to individual managers who concentrate on their own area of expertise i.e. property, bonds or equities.

Such a two stage process makes sense from an information and management point of view but has at least one major drawback. In allocating funds to each asset class which is then invested in individual properties or stocks the m ‘mutual fund’ approach is myopic, that is it ignores the covariance between individual assets or sub-classes. This implies that the segmented ‘mutual fund’ approach is sub-optimal compared with the allocation that could be produced if the covariance structure across all the assets under was considered. To what extent this segmented approach is sub-optimal is, however, unknown. This section throws some light on this issue by comparing the performance of the ‘global’ diversification strategy against the ‘segmented’ investment process. In other words does the m ‘mutual fund’ approach, which are optimised internally produce mixed-asset portfolios comparable with optimal portfolios developed from the full data set?

Two-Stage Portfolio Efficiency: An Empirical Test

The aim of this section is to compare the performance between the global optimal mixed-asset portfolio approach and that produced by allocating funds on a segmented asset class basis. One approach would be to construct the whole efficient frontier and compare the results visually. Such an approach while showing the differences between the two approaches does not provide a test of significance between the alternative investment processes. Alternatively, we could concentrate on the significance in performance of one point on the efficient frontier. This has the advantage of simplicity of comparison between the two portfolio approaches and provides a more rigorous method of analysis. In other words, in comparing the performance of the two approaches, a measure of mean-variance inefficiency between the two portfolios is required. Just such a measure is available, the significance test derived by Jobson and Korkie (1981) which examines the equivalence between the two portfolios. Consequently this is the method adopted here. But which point on the efficient frontier should be analysed?

One optimal portfolio suggest itself immediately for comparison, the portfolio with the highest Sharpe Ratio (Sharpe, 1966, 1994). This portfolios is the one offering the highest *ex-post* mean return per unit risk, and as shown by Tobin (1958), is independent of the investors’ preference structure. Consequently it is the portfolio which is most desirable to *all* investors.

The portfolio with the highest Sharpe Ratio identified by the following maximisation problem:

$$Maxq \equiv \frac{\bar{R}_p - R_f}{s_p}$$

Where:

\bar{R}_p = the expected return of portfolio p,

R_f = the risk - free rate of return,

s_p = the standard deviation of the portfolio.

In conducting the analysis the risk-free rate of return was assumed to be zero for simplicity and with no loss of generality.

The optimal portfolios with the highest Sharpe Ratios were calculated by the following method. First the weights of the mixed-asset portfolio was identified by maximising the Sharpe Ratio for the three asset classes, using the index returns of the IPMI, the FTA Index and the Long Term Bond Index. These portfolio weights were then applied to the optimal solutions produced by the individual investment returns to derive the risk and return of the mixed-asset portfolios for the global and segmented asset allocation approaches.

One difficulty with this method of analysis is the extreme holdings typically produced by optimisers, Michaud (1989). Such extreme positions, called corner solutions, seem unrealistic to most investors and against the spirit of diversification. One way to control for such extreme holdings is to place constraints (upper and lower bounds) on the amount any one asset, or group of assets, can have in the optimum portfolio (see Byrne and Lee, 1995). Thus, a second set of portfolios were calculated which had constraints on the amount of Property, Equity or Bonds in the overall allocation, but without any constraints on the allocations within the asset class. Consequently, although the overall mixed-asset allocation is within typical bounds set by institutional investors, the within asset class allocations still showed extreme and unrealistic holdings. Thus a final analysis was performed by imposing constraints on the intra-asset allocations, that is on the weights within each asset class, as well as on the mixed-asset allocations.

Using these results the equivalence or otherwise between the two portfolio optimisations, that is the ones based on the global data set and the segmented approach, were then examined by the following test of significance Z, which Jobson & Korkie (1981) have shown can be given by the following equation:

$$Z = \frac{\sigma_a(R_b - R_f) - \sigma_b(R_a - R_f)}{\sqrt{\Theta}}$$

where σ_a , σ_b and $\sigma_{a,b}$ are estimates of the standard deviation and covariance's of the excess returns of the two portfolios over the evaluation period and where Θ is calculated as follows:

$$\Theta = \frac{[\sigma_a^2 \sigma_b^2 - 2\sigma_b \sigma_{a,b} + (R_a - R_f)^2 * \sigma_b^2 / 2 + (R_b - R_f)^2 * \sigma_a^2 / 2 - (R_a - R_f)(R_b - R_f)(\sigma_{a,b}^2 + \sigma_a^2 \sigma_b^2) / 2\sigma_a \sigma_b]}{T}$$

Jobson and Korkie (1981) showing that the test statistic Z is approximately normally distributed with a zero mean and a unit standard deviation for large samples. The analysis undertaken again using a zero risk-free rate of return.

Unconstrained Intra-asset allocations

Figure 6 shows the weights of the mixed-asset portfolios derived from the index data returns for Property, Equities and Bonds. As will be appreciated, the unconstrained solution shows extreme holdings, especially in Property. Such unrealistic holdings would, consequently, be unacceptable to most investors, as suggested by Michaud (1989). To provide more realistic weights for the mixed-asset portfolio, a number of constraints need to be applied in line with the suggestion of Byrne and Lee (1995). The first constraint on the asset holdings was to put an upper bound on the allocation to Property. The upper bound was set at 15% which it can be shown is the consensus target level for Property within the institutional mixed-asset portfolio based on survey results (Lee and Byrne, 1999). This constraint, however, now produces an allocation to Bonds way above anything held by the typical UK institution investor. Consequently the next constraint imposed on the mixed-asset allocation was to set an upper bound of 30% on the holding in Bonds. The final allocation producing an allocation to the three asset classes which would not be unrealistic to UK institutional investors. All three weights were then used to control the global and segmented allocation strategies.

Figure 6: The Weights of the Mixed Asset Portfolios
Unconstrained and Constrained

	Equity	Property	Gilts
Unconstrained	36.08	57.56	6.36
Constrained ¹	26.98	15.00	58.02
Constrained ²	55.00	15.00	30.00

Notes: 1 A 15% Upper bound on Property

2 An Upper bound of 15% on Property and 30% on Bonds

Figure 7 presents the results of the two-stage allocation strategies using the global data set and the segmented approach, with no constraints on the intra-asset allocations. In other words, the individual data, either globally or segmented, is optimised to achieve the highest Sharpe Ratio and then weighted by the holdings in Figure 6 to give the resultant mixed-asset risks and returns shown in Figure 7. The results in Figure 7 highlights the insignificant difference between the two methods of investment. That is, although the global approach in all cases shows levels of return above that of the segmented method the difference is minute and insignificant, based on the results of the t-test between the two approaches. Secondly, as is to be expected, the segmented approach shows higher risk levels than the global approach, which uses the full covariance structure. However, once again, the difference is extremely small. Using the Brown-Forsythe variance test (Brown and Forsythe, 1974), there is no difference in the equality of the variances (risks) between comparable results. Thus, although the Sharpe ratios of the segmented method are all below their corresponding global approaches, there is no significant difference between the two asset allocation methods, based on the Jobson and Korkie test.

However, as suggested previously, maximising the intra-asset allocations once again produces extreme allocations or corner solutions with holdings in only a few assets. For example, without a constraint on the allocation within the property portfolio, the global allocation approach allocated all the holdings within property to the Industrial sector, especially in the Rest of the UK. Consequently, the next analysis imposes upper bounds on the allocations within the Property portfolio.

Figure 7: A Comparison in Performance of the Global and Segmented Mixed-asset Allocation
Strategies: No Constraint on Intra-asset Allocation

Mixed-asset Solutions	Method	Return	Risk	Sharpe
Unconstrained	Global	0.0090	0.0237	0.3807
Constraint on Property	Global	0.0056	0.0182	0.3064
Con. On P&G	Global	0.0090	0.0298	0.3003
Unconstrained	Segmented	0.0090	0.0239	0.3749
Constraint on Property	Segmented	0.0055	0.0182	0.3030
Con. On P&G	Segmented	0.0088	0.0298	0.2967

Constrained Intra-asset allocations

The previous analysis, whilst producing portfolios which are almost identical in terms of risk and return, using either method of construction, did so at the expense of extreme holdings in a few investments. For example, using the global allocation approach 58% of the portfolio was concentrated in Industrials, whilst the segmented method, which optimises each asset class individually, placed over 93% to the Industrial Property sector. The allocations are, thus, unrealistically high to most, if not all investors, and the results of such an analysis would have little or no practical value. Similar problems existing within the Equity portfolio, but to a lesser extent, and it was felt that no constraints were required to be imposed on this portfolio. Consequently, this section imposes constraints on the Property portfolio allocations alone to produce reasonable and acceptable portfolio solutions.

Figure 8: A Comparison in Performance of the Global and Segmented Mixed-asset Allocation
Strategies: Constraint on Property Allocation

Mixed-asset Solutions	Method	Return	Risk	Sharpe
Unconstrained	Global	0.0080	0.0222	0.3623
Con on P	Global	0.0053	0.0180	0.2962
Con on P&G	Global	0.0087	0.0295	0.2939
Unconstrained	Segmented	0.0078	0.0224	0.3492
Con on P	Segmented	0.0052	0.0179	0.2915
Con on P&G	Segmented	0.0085	0.0295	0.2892

In comparison with the comparable results in Figure 7, the portfolios in Figure 8 all have lower returns and higher risks, and, consequently, lower Sharpe Ratios, as is to be expected. Once again, there is no significant difference between the means, standard deviations and Sharpe ratios of the various portfolios. In other words, constraints produce acceptable portfolios with no significant loss in mean-variance efficiency. In addition, when we compare the segmented and global allocation methods, although the segmented approach once again shows worse performance, the differences are insignificant. In other words, whether constraints are imposed or not, the two methods of construction produce portfolios which are indistinguishable in terms of performance.

Conclusions

Based on the monthly data from January 1987 to December 1998, it can be concluded that, from the point of view of efficient diversification, little is lost by a two-stage investment process whereby funds are first allocated across the major asset classes and then individual fund managers are charged with achieving efficient intra-asset class diversification based on their knowledge and experience of the asset type. This is because the *asset* factors are more important than any *industrial* factors in determining returns.

Furthermore, the two-stage process has the advantage of potentially lower costs in terms of management and information. Given the heterogeneity of individual property assets, such specialisation may be more important than in other asset markets. In addition, once constraints on individual asset weightings are applied to the analysis, the two-stage allocation process produces asset holdings which are more realistic to investors and consequently may be followed in practice.

However, the lack of commonality between equity and real estate returns is surprising. Even with the impact of inflation removed, some common factors driving performance might have been expected. However, the results of the factor analyses and subsequent regression of sub-asset classes on property and stock factors provided no evidence to support this. Similarly, comparison of lagged values of the equity factor with the property factor did not indicate any price discovery effects. As a result, we could find no clear evidence of the expected relationships between sub-sectors across the asset class divide. It seems that the “uniqueness” of property as an asset class dominates common performance drivers between apparently similar individual sub-sectors.

Whether this lack of linkage is a measurement problem (reflecting the appraisal-based nature of property performance indices) or a more fundamental distinction requires further research. Nonetheless, as noted above, while there may be doubts concerning the reliability of property valuations, it is returns based on those valuations (and not some hypothetical true market return) that form the basis of performance measurement, benchmarking, portfolio allocation decisions and bonus calculations. This provides a stronger justification for the treatment and management of property as a distinct asset class providing diversification benefits within the mixed asset portfolio.

References

- Barkham, R. and Geltner, D. (1995) Price Discovery in American and British Property Markets, *Real Estate Economics*, **23**, 21-44.
- Brown, M. and Forsythe, A. (1974) Robust Tests For the Equality of Variances, *Journal of the American Statistical Association*, **69**, 364-367.
- Byrne, P. and Lee, S. (1995) Is There a Place For Property in the Multi-Asset Portfolio? *Journal of Property Research*, **6**, 60-83
- Cuthbertson, K., Hayes, S. and Nitzsche, D. (1999) Market Segmentation and Stock Price Behaviour, *Oxford Bulletin of Economics and Statistics*, **61**, 2, 217-235
- Dimson, E. (1979) Risk Measurement When Shares are Subject to Infrequent Trading, *Journal of Financial Economics*, **7**, 197-226.
- Dimson, E. and Marsh, P. (1983) The Stability of UK Risk Measures and the Problem of Thin Trading, *Journal of Finance*, **38**, 3, 753-783.
- Drummen, M. and Zimmerman, H. (1992) The Structure of European Stock Returns, *Financial Analysts Journal*, July/August, 15-26.
- Geltner, D. (1993) Estimating Market Values from Appraisal Values Without Assuming an Efficient Market, *Journal of Real Estate Research*, **8**, 3 325-345.
- Jobson, J. and Korkie, B. (1981) Performance Hypothesis Testing with the Sharpe and Treynor Measures, *Journal of Finance*, **36**, 4, 889-906.
- Lee, S. and Byrne, P. (1999) Some Implications of the Lack of a Consensus View of UK Property's Future Risk and Return, *Journal of Property Research*, **16**, 3, 257-270.
- Lizieri, C. and Satchell, S. (1997) Interactions Between Property and Equity Markets: An Investigation of the Linkages in the UK 1972-1992, *Journal of Real Estate Finance & Economics*, **15**, 11-26.
- Michaud, R. (1989) The Markowitz Optimisation Enigma: is 'Optimised' Optimal? *Financial Analysts Journal*, January/February, 31-42
- Sharpe, W. (1966) Mutual Fund Performance, *Journal of Business*, **39**, (Jan), 119-138.
- Sharpe, W. (1994) The Sharpe Ratio, *Journal of Portfolio Management*, Fall, 49-58.
- Tobin, J. (1958) Liquidity Preference as Behavior Toward Risk, *Review of Economic Studies*, February.